

USING NEURAL NETWORKS TO ESTIMATE MOTION VECTORS FOR MOTION CORRECTED PET IMAGE RECONSTRUCTION

CROSS REFERENCE TO CO-PENDING APPLICATION

[0001] This application claims priority to U.S. Provisional Patent Application No. 63/003,238, filed Mar. 31, 2020, the contents of which are incorporated herein by reference.

FIELD OF THE INVENTION

[0002] The present invention is directed to a method and system for providing improved motion compensation in images (e.g., medical images), and, in one embodiment, to a method and system for using a deep learning neural network based system to provide motion correction for PET data.

BACKGROUND

[0003] Artifacts caused by patient breathing and movement during positron emission tomography (PET) data acquisition affect image quality and lead to underestimation of tumor activity and overestimation of tumor volume. See, e.g., [Kalantari 2016]: (Kalantari F, Li T, Jin M and Wang J; 2016; Respiratory motion correction in 4D-PET by simultaneous motion estimation and image reconstruction (SMEIR) *Phys Med Biol* 61 5639). Lesion detectability also suffers from motion blurring since small lesions are likely to remain undetected, which may result in misdiagnosis. See, e.g., [Nehmeh 2002b]: (Nehmeh S A, Erdi Y E, Ling C C, Rosenzweig K E, Schoder H, Larson S M, Macapinlac H A, 384 Squire O D and Humm J L; 2002; Effect of respiratory gating on quantifying PET images of lung cancer *J Nucl Med* 43 876-81). This makes motion corrected image reconstruction valuable for PET imaging. Respiratory gating has been used to gate list-mode PET data into multiple bins over a respiratory cycle based on either an external hardware or a data-driven self-gating technique. See, e.g., (1) [Chan 2017]: (Chan C, Onofrey J, Jian Y, Germino M, Papademetris X, Carson R E and Liu C 2017 Non-rigid event-by-event continuous respiratory motion compensated list-mode reconstruction for PET *IEEE transactions on medical imaging* 37 504-15), and (2) [Büther 2009]: (Büther F, Dawood M, Stegger L, Wübbeling F, Schäfers M, Schober O and Schäfers K P 2009 List mode-driven cardiac and respiratory gating in pet *J Nucl Med* 50 674-81). Within each time bin, the motion blurring is assumed to be negligible. See, e.g., [Nehmeh 2002a]: (Nehmeh S, Erdi Y, Ling C, Rosenzweig K, Squire O, Braban L, Ford E, Sidhu K, Mageras G and Larson S 2002a Effect of respiratory gating on reducing lung motion artifacts in PET imaging of lung cancer *Med Phys* 29 366-71). The motion-frozen images can be reconstructed gate-by-gate using the data from each bin. However, gated PET reconstructed images suffer from low signal-to-noise ratio since the count level is low in each gate. Furthermore, non-rigid registration of respiratory-gated PET images can reduce motion artifacts and preserve count statistics, but it is time consuming.

[0004] All motion corrected image reconstruction techniques, whether they perform motion correction post-reconstruction or during the reconstruction, require motion vectors. These motion vectors describe how each voxel moves

from one gate to another. Motion vectors are typically estimated by reconstructing the individual gates and then registering each gate to the reference gate. Since image registration techniques deform one gate to another, the output of a registration describes how one gate should be deformed to obtain another gate and these deformation fields form the motion vectors of interest. Image registration techniques only deal with transforming a gated image such that it looks like another gated image as closely as possible. There is no requirement of generating physically realistic motion vectors. As a result, an image registration technique can produce physically unrealistic deformation fields where voxels cross each other or move unrealistically long distances or get compressed beyond physical limits. The drawbacks of image registration techniques are dealt with by using techniques such as regularizing deformation fields and/or applying the techniques in a multi-resolution framework. Even when image registration techniques are made to produce realistic motion vectors, they are computationally intensive as each image registration corresponds to solving an optimization problem. Furthermore, if the reference gate is changed, a whole new set of registration processes need to be performed.

[0005] One of the widely used methods to reduce noise is to utilize events from all gates by incorporating a motion model into the reconstruction procedure. While the motion information can be obtained from high resolution anatomical images, e.g. computed tomography (CT) (See, e.g., [Lamare 2007]: (Lamare F, Carbayo M L, Cresson T, Kontaxakis G, Santos A, Le Rest C C, Reader A and Visvikis D 2007 List-mode-based reconstruction for respiratory motion correction in PET using non-rigid body transformations *Phys Med Biol* 52 5187)) or magnetic resonance imaging (MM) (See, e.g., [Fayad 2015]: (Fayad H, Schmidt H, Wuerslin C and Visvikis D 2015 Reconstruction-incorporated respiratory motion correction in clinical simultaneous PET/MR imaging for oncology applications *J Nucl Med* 56 884-9)), utilizing other image modalities always leads to multiple issues, such as extra time and cost, image co-registration, extra radiation dose from the CT scan and synchronization issues between the scanners. Accurate non-rigid registration based on gated PET images themselves is challenging due to their high noise levels and is also time consuming. Recently, deep learning techniques have provided new approaches for either supervised image registration (See, e.g., (1) [Sokooti 2017]: (Sokooti H, de Vos B, Berendsen F, Lelieveldt B P, Išgum I and Staring M 2017 3D Convolutional Neural Networks Image Registration Based on Efficient Supervised Learning from Artificial Deformations *International Conference on Medical Image Computing and Computer-Assisted Intervention* 232-9), and (2) [Krebs]: (Krebs J, Mansi T, Delingette H, Zhang L, Ghesu F C, Miao S, Maier A K, Ayache N, Liao R and Kamen A 2017 Robust non-rigid registration through agent-based action learning *International Conference on Medical Image Computing and Computer-Assisted Intervention* 344-52)) or unsupervised image registration (See, e.g., (1) [Bakakrishnan 2018]: (Balakrishnan G, Zhao A, Sabuncu M R, Guttag J and Dalca A V 2018 An Unsupervised Learning Model for Deformable Medical Image Registration *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* 9252-60), (2) [Li and Fan 2018]: (Li H and Fan Y 2018 *IEEE 15th International Symposium on Biomedical Imaging* 1075-8), and (3) [Lau 2019]: (Lau T, Luo J, Zhao S, Chang E I and